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Detection of COVID-19 Enhanced by a Deep Extreme Learning Machine

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Abstract: The outbreak of coronavirus disease 2019 (COVID-19) has had a tremendous effect on daily life and a great impact on the economy of the world. More than 200 countries have been affected. The diagnosis of coronavirus is a major challenge for medical experts. Early detection is one of the most effective ways to reduce the mortality rate and increase the chance of successful treatment. At this point in time, no antiviral drugs have been approved for use, and clinically approved vaccines have only recently become available in some countries. Hybrid artificial intelligence computer-aided systems for the diagnosis of disease are needed to help prevent the rapid spread of COVID-19. Various detection methods are being used to diagnose coronavirus. Deep extreme learning is the most successful artificial intelligence (AI) technique that efficiently supports medical experts in making smart decisions for the detection of COVID-19. In this study, a novel detection model to diagnose COVID-19 has been introduced to achieve a better accuracy rate. The study focuses on quantitative analysis and disease detection of COVID-19 empowered by a statistical real-time sequential deep extreme learning machine (D2C-RTS-DELM). The experimental results show 98.18% accuracy and 98.87% selectivity, and the probability of detection is 98.84%. The results demonstrate that the quantitative analysis and statistical real-time sequential deep extreme learning machine used in this study perform well in forecasting COVID-19 as well as in making timely decisions for treatment.

Keywords: COVID-19; deep extreme learning machine; real-time sequential analysis; infectious disease; smart decision; hybrid artificial intelligent systems

1 Introduction

The rapid spread of the novel coronavirus threatens many lives and has affected the economy of the world. The outbreak was originally reported in December 2019 in the city of Wuhan, China, and a pandemic was later announced by the World Health Organization (WHO) [1]. Coronavirus disease 19 (COVID-19) is a highly infectious viral disease, and it is critical to control its spread. Some of the most common symptoms of COVID-19 are cough, shortness of breath, and breathing difficulties. Fever is considered to be one of the typical clinical symptoms of COVID-19 [2]. Therefore, screening for suspected cases of fever in infected areas and their surroundings has been comprehensively implemented. Various preventive measures have been taken to reduce contact between individuals including avoiding mass gatherings, limiting population mobility, closing educational institutions, and encouraging work-from-home arrangements.

The early detection of COVID-19 can determine the chances of successful remedial action and the survival of patients. However, the diagnosis of COVID-19 has become a great challenge for medical practitioners [3]. The spread of COVID-19 has been controlled in China but remains a threat all over the world. Thus, it has become very urgent to develop computer-aided systems to assist medical experts in the control of the disease [4]. In this context, artificial intelligence (AI) has led to many useful applications, especially in the medical domain. Recently, many AI applications and methods have been developed to fight against the coronavirus with the help of medical data analytics, natural language processing, text mining, the Internet of Things (IoT), and image processing [5].

Many researchers looked at ways to prevent the spread of COVID-19 by utilizing deep learning and machine learning approaches. Deep learning can extract features from medical images [6]. In an earlier study [7], researchers developed a model based on a machine learning technique that consists of an adaptive network-based fuzzy and multilayer perceptron to deal with the rapidly spreading pandemic. In other research [8], a system to detect the extent of coronavirus through cloud computing and machine learning was proposed. X-rays and computer tomography (CT-scan) are also being used in some studies to find symptoms of COVID-19 [9]. A previous study [10] investigated the prediction of coronavirus in various countries including the United States of America. The predicted machine learning time series was used to analyze the active, infected, and cured cases for COVID-19. Much information is accessible on the internet in the form of graphical and numerical data. The statistical analysis of available information using machine learning can provide better results to overcome the challenges around the globe facing businesses, medicine, commerce, and economics [11].

This paper describes the detection of COVID-19 and a deep machine learning approach that can be applied to solve the challenges of this pandemic. The main contributions are the following.

a) We formulate an optimization problem in which the objective is to obtain maximum accuracy and a minimum miss rate of COVID-19 detection.
b) A quantitative analysis and detection of COVID-19 is empowered by a statistical real-time sequential deep extreme learning machine (D2C-RTS-DELM) that is proposed for the real-time detection of COVID-19.
c) We compare the proposed model with other studied algorithms like Support Vector Machine (SVM) and Linear Regression (LR). Simulation results have shown that the proposed algorithm gives good results compared to previously published approaches like SVM and LR.

2 Literature Review

The COVID-19 pandemic has increased the need for rapid medical decisions and efficient use of healthcare resources. Zhang et al. [12] developed a Confidence Aware Anomaly Detection (CAAD) model for the screening of viral pneumonia using chest X-ray images. The proposed model is based on three modules, namely a feature extractor, anomaly detection, and confidence prediction. The X-VIRAL dataset was used to train the proposed model, and the XCOVID dataset was also used to test the model. The experimental results showed 83.61% accuracy and 71.79% sensitivity for the proposed model.

Batista et al. [13] designed a system based on a machine learning technique for the prediction of COVID-19. The researchers focused only on patients admitted to emergency care. Different types of algorithms including gradient boosting trees, random forests, support vector machine neural networks, and logistic regression were applied to train the model. The experimental results showed that the support vector machine algorithm achieved 85%, 68%, 85%, and 16% of accuracy, sensitivity, specificity, and brier score, respectively, a performance that was better than the other four algorithms for the prediction of COVID-19.

Wu et al. [14] proposed a COVID-19 prediction model based on a random forest algorithm. In the study, 11 significant indices were derived from 49 indices obtained from clinical blood tests for the identification of coronavirus. The proposed method showed 95.95% overall accuracy that helps medical experts make timely decisions and treatment.

Farooq et al. [15] suggested a framework based on a convolutional neural network for the screening of COVID-19. COVID-ResNet resized input images to fine-tune the network at all stages. The experimental results showed the accuracy was 96.23% and confirmed the computational efficiency of the proposed method. Maghdid et al. [16] stated that there is a need to develop a rapid and accurate artificially intelligent tool to detect COVID-19. This task is challenging due to the lack of availability of the dataset. The researchers proposed a model based on transfer learning algorithms and deep learning techniques. A Convolutional Neural Network and pre-trained AlexNet model have been applied to Computer Tomography scan and X-ray image datasets. The proposed model outperforms existing methods and achieved an accuracy up to 98% using a pre-trained network and 94.1% accuracy with a modified Convolutional Neural Network.

Rustam et al. [17] explored machine learning-based prediction models and demonstrated their importance to improve decision making for future actions. The proposed research established the ability of machine learning models to predict COVID-19 in patients. Various models like the Least Absolute Shrinkage and Selection Operator (LASSO), Exponential Smoothing (ES), Linear Regression (LR), and Support Vector Machine (SVM) were used to predict coronavirus infections. Each model forecast three types of prediction such as the number of deaths, recoveries, and newly infected cases. The extensive experimental results of the study showed that an exponential smoothing algorithm performed best among all the models.

Yousaf et al. [18] developed an Auto-Regressive Integrated Moving Average (ARIMA) model to forecast COVID-19. The proposed forecasting model predicted coronavirus-confirmed cases, the number of recoveries, and the number of deaths in Pakistan. The model forecasted at a 95% prediction interval 168–885, 2391–16126, and 5681–33079 number of deaths, recoveries, and confirmed cases, respectively.

He et al. [19] designed a novel discrete-time stochastic model for the prediction and control of COVID-19. The proposed model used binomial distributions to reveal the transmission of coronavirus. The proposed model predicted that the number of new cases declined with time, and the total number of confirmed cases reached a maximum.

Wu et al. [20] proposed a Joint Classification and Segmentation (JCS) system to diagnose COVID-19 in real-time. The researchers constructed a large-scale dataset that consisted of 144,167 computer tomography images. The proposed classification system identified whether patients suspected to have COVID-19 were negative or positive by visual examination. The researchers applied a segmentation system to determine fine-grained lesion regions in computer tomography images of coronavirus patients for pixel-level prediction. The experimental results demonstrated an average specificity of 93.0% and sensitivity of 95.0% for the classification. The proposed model achieved a 78.3% dice score for segmentation that proved its efficiency.

Ozturk et al. [21] developed a novel model to automatically detect COVID-19 using deep neural networks. The proposed model used a dataset of X-ray images and two types of classification, namely binary and multiclass. The binary classification achieved 98.08% accuracy, while the multiclass classification achieved 87.02% accuracy. The model is helpful for radiologists to detect coronavirus and can also be used to detect other chest-related diseases. Machine learning play a very important in various domains of life like medical, smart energy, wireless communication, business intelligence and smart city [22–27].

This study evaluates detection methods for COVID-19 and presents a comprehensive review of previous studies. Furthermore, the study discusses various types of artificial intelligence, machine learning, and deep learning methods for quantitative analysis.

3 Proposed D2C-RTS-DELM System Model

Artificial intelligence plays an important role in many areas of life. In particular, the enhancement of deep learning techniques has revolutionized the medical sciences. The proposed D2C-RTS-DELM system model used for the detection of COVID-19 and quantitative analysis is shown in Fig. 1. The model is divided into two phases, namely the training and validation phases. In the training phase, the data acquisition layer collects information from the Electronic Medical Records (EMR) of patients. The collected data consist of various parameters such as fever, shortage of breath, headache, chest pain, cough, and flu. After data collection, the preprocessing layer adjusts for missing values and controls various errors that occur in the collected dataset. The average value is used by the method to remove ambiguities from the dataset and to complete the transformation into structured data.

The proposed D2C-RTS-DELM model comprises two layers, namely the application and performance layers. In the application layer, a deep extreme learning machine approach is applied to train the model. After the application layer, the performance layer is active and evaluates the proposed model in the context of accuracy, miss rate, and other parameters. If the learning criteria do not meet the required values, then the model needs to be retrained. In contrast, if the learning criteria do meet the required values, then they are stored in the cloud. The second phase of the proposed D2C-RTS-DELM is the validation phase.

In the validation phase, the data acquisition layer collects details from the Electronic Medical Record (EMR). The collected data consist of various parameters such as fever, shortage of breath, headache, chest pain, cough, and flu. After data collection, the preprocessing layer adjusts for missing values and controls various errors that occur in the collected dataset. The average value is used by the method to remove ambiguities from the dataset and turns the information into structured data. Next, the proposed D2C-RTS-DELM model is imported from the cloud to validate the model. If the coronavirus is not detected, then the proposed model discards the case. If COVID-19 is detected, the case is referred to the hospital.

A deep extreme learning machine (DELM) is used to train the single hidden layer for a feed-forward neural network. In contrast, the deep extreme learning machine applies various learning approaches including back-propagation input weights that are randomly initialized. DELM updates output weights in an iterative mode, and the input weights remain the same. In this way, DELM can learn quickly. The DELM method has multiple hidden layers of feed-forward neural networks including z hidden layer neurons and a training dataset of Z records (ψ_m, y_m).

The deep extreme learning machine operates as follows: $\psi_m \in A_i$ and $y_m \in A_j$. The outcome of these multiple hidden layer feed-forward neural networks is:

$$\sum_{k=1}^{z} \eta_k \delta \left(\mathbf{V}_k \ni_{\mathrm{m}} + \boldsymbol{v_k}\right), \qquad m \in [1, Z] \tag{1}$$

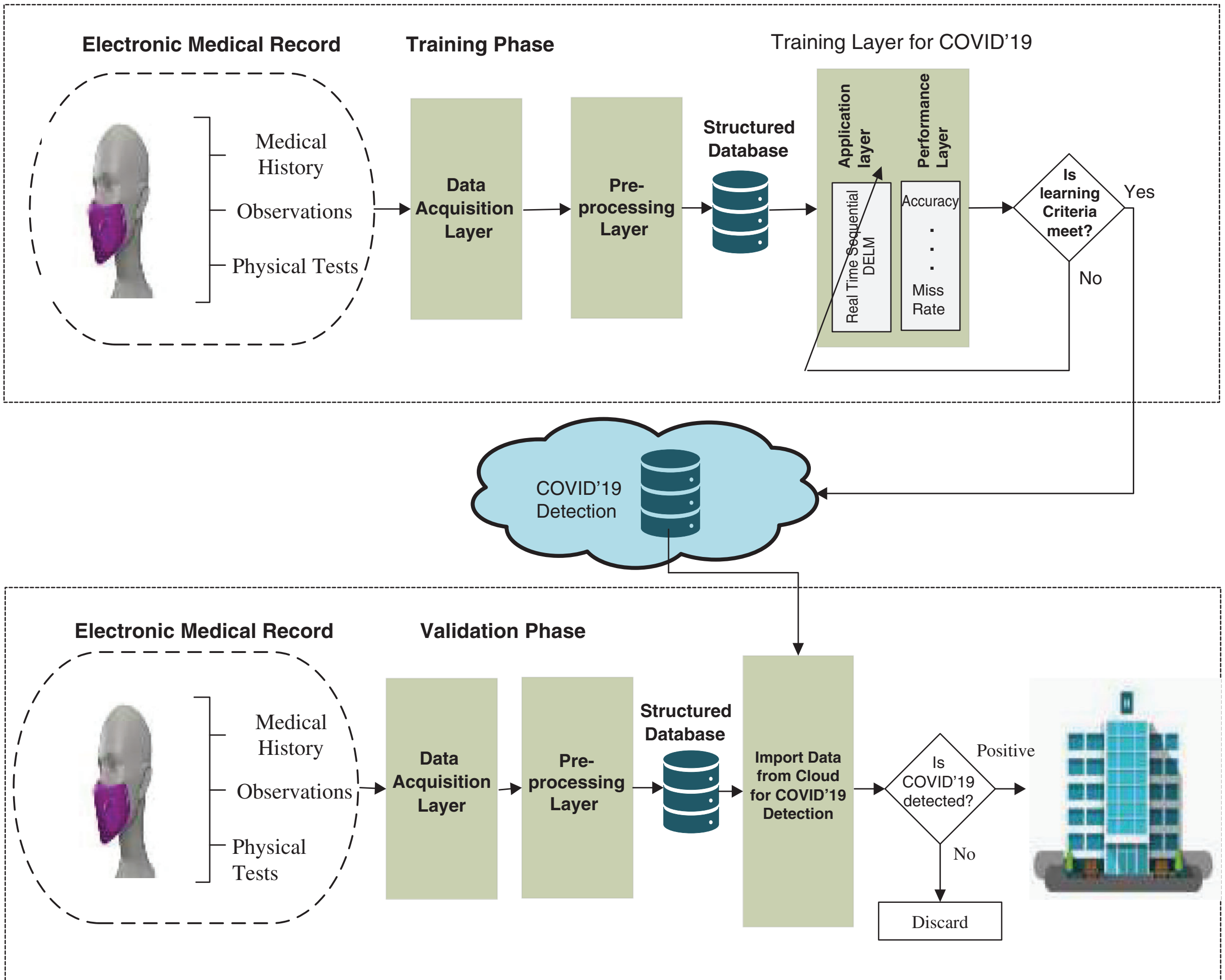

Figure 1: Proposed D2C-RTS-DELM system model

Here the learning variables are $\mathbf{v}_k$ and x_k, the node output is η_k at weight k, and $\delta : \mathrm{A} \rightarrow \mathrm{A}$ is the activation function.

An ideal reconciliation of the multiple hidden layer feed-forward neural network with zero error clarifies that with discrete intervals $\mathbf{V}_k$ and x_k η_k occurs such that:

$$\sum_{k=1}^{z} \eta_k \delta(\mathbf{V}_k \ni_{\mathrm{m}} + x_k) = \mathrm{y}_m \qquad m \in [1, Z] \tag{2}$$

This can be presented as follows:

$$\mathbf{O}\eta = \mathbf{W} \tag{3}$$

where

$$\mathbf{O} = \begin{bmatrix} \delta(\mathbf{V}_1 \ni_1 + x_1) & & \delta(\mathbf{V}_z \ni_1 + x_z) \\ \vdots & \cdots & \vdots \\ \vdots & & \vdots \\ \delta(\mathbf{V}_1 \ni_Z + x_1) & & \delta(\mathbf{V}_z \ni_Z + x_z) \end{bmatrix} \tag{4}$$

and

$$\eta = \left(\eta_1^T \ldots \eta_z^T\right)^T, \ \mathbf{W} = \left(y_1^T \ldots y_Z^T\right)^T \tag{5}$$

The outcome weights value can be solved for the known number of observations of the hidden layer neurons by using the following relationship:

$$\eta = \mathbf{O}^{-1}\mathbf{W} \tag{6}$$

$\mathbf{O}^{-1}$ is the inverse of matrix $\mathbf{O}$. The deep extreme machine learning represents a compressive computational model suitable for this study.

The deep extreme learning machine is a batch learning model. A real-time sequential deep extreme learning machine is proposed to handle the information received in sequence. In the case of new information, D2C-RTS-DELM upgrades the batch learning framework that works without previously trained data.

D2C-RTS-DELM contains two learning stages, namely the initial and sequential stages. In the initial stage, the model trains using the different observation range of Z_0, and these observations represent the performance of the hidden layer cultivate matrix $\mathbf{O}_0$. In the deep extreme learning machine and the real-time sequential deep extreme learning machine, Z_0 should be same as $\mathbf{O}_0$, or the hidden layer neurons n should be greater than the level of $(\mathbf{O}_0)$ when it is equivalent to and greater than z. The sequence of steps for the model can be updated for new information following the initial step.

Let $\{(\ni m, \mathbf{y}m)\}_{m=1}^{Z_0}$represent the given training dataset at the earliest stage. $\mathbf{O}_0$ and η_0 are the hidden layer performance matrix. The weights of the output layer of DELM are as follows:

$$\mathbf{O}_0 = \begin{bmatrix} \delta(\mathbf{V}_1 \ni_1 + x_1) & & \delta(\mathbf{V}_z \ni_1 + x_z) \\ \vdots & & \vdots \\ \vdots & \cdots & \vdots \\ \delta(\mathbf{V}_1 \ni_{Z_0} + x_1) & & \delta(\mathbf{V}_z \ni_{Z_0} + x_z) \end{bmatrix} \tag{7}$$

$$\eta_0 = \mathbf{P_0 O_0^T W_0} \tag{8}$$

where $\mathbf{P_0} = \left(\mathbf{y_1^T O_0}\right)^{-1}$ and $\mathbf{W_0} = \left(\mathbf{y}_1^T \ldots y_{Z_0}^T\right)^T$.

After the initial stage, namely the creation of the $(l+1)^{\text{th}}$ record with Z^{l+1} number of records, the partially hidden layer performance matrix is as follows:

$$\mathbf{O_{l+1}} = \begin{bmatrix} \delta\left(\mathbf{V}_1 \ni_{\left(\sum_{k=0}^{l} Z_k\right)+1} + x_1\right) & & \delta\left(\mathbf{V}_z \ni_{\left(\sum_{k=0}^{l} Z_k\right)+1} + x_z\right) \\ \vdots & & \vdots \\ \vdots & \cdots & \vdots \\ \delta\left(\mathbf{V}_1 \ni_{\left(\sum_{k=0}^{l} Z_k\right)+1} + x_1\right) & & \delta\left(\mathbf{V}_z \ni_{\left(\sum_{k=0}^{l} Z_k\right)+1} + x_z\right) \end{bmatrix} \tag{9}$$

The performance weights can be modified using the following:

$$\boldsymbol{\eta}_{\mathbf{l+1}} = \boldsymbol{\eta}_{\mathbf{l}} + \mathbf{P_{l+1} O_{l+1}^T} (\mathbf{W_{l+1}} - \ \mathbf{O_{l+1}} \boldsymbol{\eta}_{\mathbf{l}} \tag{10}$$

with

$$\mathbf{P_{l+1}} = \mathrm{P_l} + \mathbf{P_l O_{l+1}^T}\left(\mathbf{B} + \mathbf{O_{l+1} P_l O_{l+1}^T}\right)^{-1} \mathbf{O_{l+1}} \mathrm{P_l} \tag{11}$$

The back-propagation method involves weight configuration, feed-forward propagation, backward error propagation, and a distinguishability update. An activation function like $\mathrm{g}(a) = sigmoid$ is present in the hidden layer for each neuron. This approach helps to design the sigmoid input function and the DELM hidden layer:

$$Error = \frac{1}{2}\sum\nolimits_{k}(ak - fv_k)2 \tag{12}$$

a_k = desired output

fv_k = calculated output

Eq. (12) specifies a back-propagation error, which can be measured by dividing the square sum from the required output by 2. The weight adjustment is needed to mitigate the common error. The weight change levels for the output layer are shown in Eq. (13) as follows:

$$\Delta \mathrm{C}_{m,k}^{q=6} \propto -\frac{\partial \mathrm{S}}{\partial \mathrm{C}^{q=6}} \tag{13}$$

$i = 1, 2, 3 \ldots\ldots\ldots 10 \ (no.\ of\ neurons)$

and k = Layer of Output Value

Eq. (14) illustrates the weights update and how the biases occur between the hidden layer and inputs:

$$C_{m,z}^{q}(d) = C_{m,z}^{q}(d+1) + €\Delta C_{m,k}^{q} \tag{14}$$

4 Simulation Results and Discussions

The proposed real-time sequential deep extreme learning machine (D2C-RTS-DELM) model was evaluated for its ability to perform quantitative analysis and disease detection for COVID-19. The Matlab tool 2019a was used for simulation and evaluation purposes for the proposed model. The dataset of COVID-19 patients used in this study was obtained from the Service Hospital, Lahore, Pakistan. The dataset consisted of 547 Electronic Medical Records (EMR), and 80% of these records were used for training. The remaining 20% of samples were used to evaluate the proposed D2C-RTS-DELM model. The D2C-RTS-DELM model was evaluated for different statistical parameters including accuracy, miss rate, probability of detection (PD), selectivity, false omission rate, probability of false alarm (PFA), and false discovery rate:

$$\text{Accuracy} = \frac{\sum \text{True positive} + \text{True negative}}{\sum \text{Total instances}} \tag{15}$$

$$\text{Miss rate/False negative rate} = \frac{\sum \text{False negative}}{\sum \text{Condition positive}} \tag{16}$$

$$\text{Probability of detection (PD)} = \frac{\sum \text{True positive}}{\sum \text{Condition positive}} \tag{17}$$

$$\text{Selectivity} = \frac{\sum \text{True negative}}{\sum \text{Condition negative}} \tag{18}$$

$$\text{False omission rate} = \frac{\sum \text{False negative}}{\sum \text{Predicted condition negative}} \tag{19}$$

$$\text{Probability of false alarm (PFA)} = \frac{\sum \text{False positive}}{\sum \text{Condition negative}} \tag{20}$$

$$\text{False discovery rate} = \frac{\sum \text{False positive}}{\sum \text{Predicted condition positive}} \tag{21}$$

The proposed D2C-RTS-DELM model detects positive and negative cases of COVID-19

The training data for the proposed D2C-RTS-DELM model for the purpose of detecting COVID-19 are shown in Tab. 1. A total of 547 of EMR samples were used for training and validation purposes. In the training phase, 80% of EMR samples were used to train the proposed D2C-RTS-DELM model. A total of 437 training samples were further divided into two groups of positive and negative samples. In the positive cases, the proposed D2C-RTS-DELM model predicted 170 samples correctly and 3 samples incorrectly. In the negative case, the proposed D2C-RTS-DELM model predicted 262 samples correctly and only two samples incorrectly.

Table 1: Training of the proposed D2C-RTS-DELM model during the detection of COVID-19

Proposed D2C-RTS-DELM model training of EMR samples (80%)			
Total EMR samples (T = 437)		Expected output (μ_p, μ_n)	
		μ_p (COVID-19 positive)	μ_n (COVID-19 negative)
Input	p = 173 Positive	170	03
	n = 264 Negative	02	262

The validation data for the proposed D2C-RTS-DELM model for the purpose of detecting COVID-19 are shown in Tab. 2. A total of 20% of EMR samples were used to validate the proposed D2C-RTS-DELM model. A total of 110 EMR validation samples were further divided into positive and negative groups. In the positive cases, the proposed D2C-RTS-DELM model predicted 42 samples correctly and 1 sample incorrectly. In the negative cases, the proposed D2C-RTS-DELM model predicted 66 samples correctly and only one sample incorrectly.

The performance of the proposed D2C-RTS-DELM model in terms of accuracy, miss rate, probability of detection, selectivity, false omission rate, probability of false alarm, and false discovery rate during both phases of training and validation is shown in Fig. 2. The proposed D2C-RTS-DELM model during training achieved 98.86%, 1.14%, 98.84%, 98.87%, 0.76%, 1.13%, and 1.73% accuracy, miss rate, probability of detection, selectivity, false omission rate, probability of false alarm, and false discovery rate, respectively.

Table 2: Validation of the proposed D2C-RTS-DELM model during the detection of COVID-19

Proposed D2C-RTS-DELM model Validation of EMR samples (20%)			
Total EMR samples (T = 110)		Expected output (μ_p, μ_n)	
		μ_p (COVID-19 positive)	μ_n (COVID-19 negative)
Input	p = 43 Positive	42	01
	n = 67 Negative	01	66

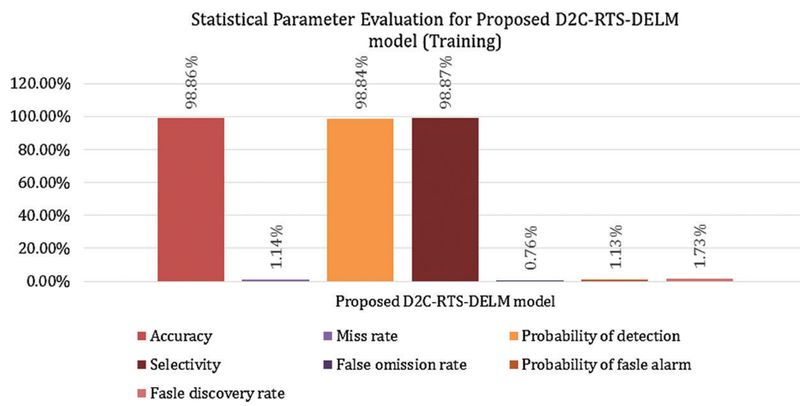

Figure 2: Statistical measures for proposed D2C-RTS-DELM model (training)

The performance of the proposed D2C-RTS-DELM modeling terms of accuracy, miss rate, probability of detection, selectivity, false omission rate, probability of false alarm, and false discovery rate during both phases of training and validation is shown in Fig. 3. In the validation phase, the proposed D2C-RTS-DELM model achieved 98.86%, 1.14%, 98.84%, 98.87%, 0.76%, 1.13%, and 1.73% of accuracy, miss rate, probability of detection, selectivity, false omission rate, probability of false alarm, and false discovery rate, respectively.

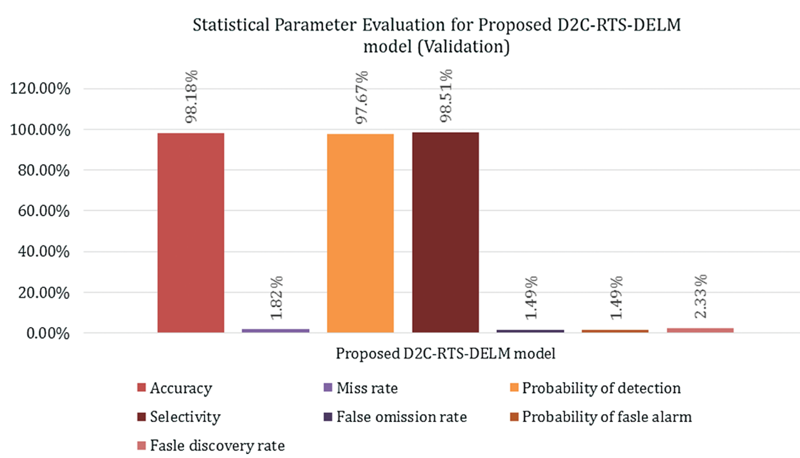

Figure 3: Statistical measures for proposed D2C-RTS-DELM model (validation)

The performance of the proposed D2C-RTS-DELM model using real-time sequential deep extreme learning machines compared with the state-of-the-art approaches given in the literature is shown in Fig. 4. The approaches used for comparison were as follows: SVM [12], SVM [13], SVM [14], LR/CNN [15], and CNN [16].

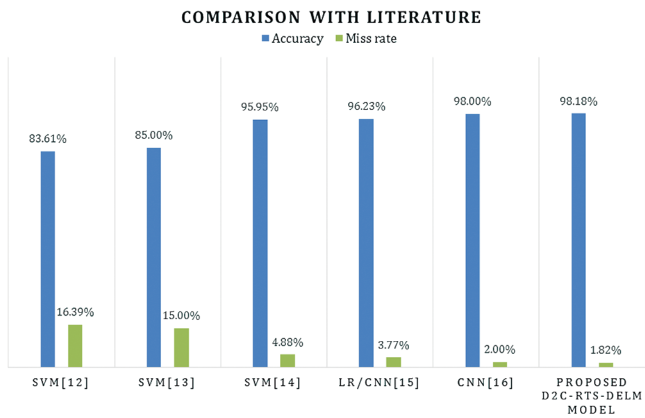

Figure 4: Performance evaluation of the proposed D2C-RTS-DELM model compared with studies in the literature

5 Conclusion

The spread of COVID-19 has threatened human life around the world. Early detection is essential for treatment and survival. The present study describes the quantitative analysis and a statistical real-time sequential deep extreme learning machine for the prediction of COVID-19. The proposed study not only forecasts coronavirus but also provides great help to medical practitioners in making timely decisions to alleviate the coronavirus crisis. The real-time sequential method is the primary focus of this study. The accuracy, miss rate, probability of detection, selectivity, false omission rate, probability of false alarm, and false discovery rate for D2C-RTS-DELM were 98.18%, 98.86%, 1.14%, 98.84%, 98.87%, 0.76%, 1.13%, and 1.73%, respectively. The experimental results are comparable to other state-of-the-art methods. D2C-RTS-DELM should prove to be a useful tool for clinical experts to control the spread of COVID-19.

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Limitations and Future Work: The proposed D2C-RTS-DELM model-based solution required more computational complexity compared with SVM. Different techniques may be used in the future to generate high scores in decision accuracy and policy including combinations of Convolutional Neural Network (CNN), Variational Auto Encoder (VAE), Mixed Density Network (MDN), Recurrent Neural Network (RNN), Genetic Algorithms (GA), and Evolution Strategies (ES).

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